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How Do Homes Transfer Across The Income Distribution? The Role of Supply Constraints*

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Abstract

We estimate the effects of supply constraints on home transfers across the income distribution as they age. Using matched data on transactions to buyer and seller income, we document significant upward filtering of homes from sellers to buyers, at +0.3% to +0.4% per home-year. However, there is considerable heterogeneity spatially and over the relative income distribution. A change in local planning laws identifies the causal impact of supply constraints. Instrumenting for them, filter rates are zero or negative in line with theory. Low-income buyers are more affected by supply constraints than high-income buyers. Removing supply constraints boosts filtering.

Keywords: Filtering, Housing Supply Constraints, Household Income
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1. Introduction

The longstanding debate on policies designed to increase access to affordable housing for the poor has come to the fore in recent decades. Housing prices are growing more rapidly than income, and home-ownership rates are declining. While regulatory constraints on the supply of new homes can reflect local residents' preferences and the desire by policymakers to have them built with a minimum quality, energy efficiency and safety, they are also thought to be important for the decline in housing affordability.

Do regulatory constraints on supply (hereafter supply constraints) matter for the distribution of housing prices, income, and urban movement? In one view, reducing them would do little to alter housing prices or income, as there is limited direct evidence that supply constraints affect affordability and relaxing them is unlikely to stimulate migration to more productive neighborhoods (Rodríguez-Pose and Storper, 2020). The alternative view is that, coupled with rising demand, supply constraints raise prices, reduce affordability, and distort individual housing and location decisions that together have significant micro and macro consequences.[1]

Crucial to this debate is whether households on low and middle incomes can purchase homes. Yet, direct evidence on how homes transfer across the income distribution remains sparse.[2] Evidence on how supply constraints affect those transfers is largely non-existent (Molloy, 2020). In this paper we use a unique data set on private home sales, matched to buyer and seller income, to provide the first direct evidence on how supply constraints affect home transfers across the income distribution, also known as filtering.

Filtering is the dynamic process whereby existing homes are transferred from high- to middle- to low-income households, as they depreciate with age.[3] It is a key mechanism for the supply of homes to low-income households, as developers build little unsubsidized housing for the poor (Rosenthal, 2014, Baer, 1986). Filtering is important for understanding how homes transfer across the income distribution, and its quantitative impact matters for the design of affordable housing policies such as rental or home purchase subsidies, subsidies for new construction, or for reducing supply constraints (Molloy et al. (2022), Mast (2021), Nathanson (2020), Braid (1984), Sweeney (1974)).[4]

[1] See for example, Manville, Lens, and Monkkonen (2022), Hsieh and Moretti (2019), Glaeser and Gyourko (2018), Ganong and Shoag (2017), Hilber and Vermeulen (2015).

[2] The notable exceptions are Rosenthal (2014) and Liu, McManus, and Yannopoulos (2021) who document new facts on housing transfers and income (filtering) across buyers for the US.

[3] Theoretical models predict that homes should filter down the income distribution to buyers with lower income on average over time (e.g. Sweeney (1974), Ohls (1975), Braid (1984) and Nathanson (2020)).

[4] It is thus a natural (though not the only) measure for assessing housing affordability. Other concepts

The standard approach to estimate filtering, due to Rosenthal (2014), is to difference across the income of different buyers of the same home between resales. This repeat-buyer-income model avoids the well known problem that omitted home attributes, that capture a home's quality, are correlated with income and so estimates without differencing are biased. Implementing this approach requires a long time series of market sales or survey data, homes with attributes and implicit prices that remain unchanged between resales, and resales that are not affected by selection.[5]

Like Rosenthal (2014), we estimate filtering using differences in income when homes are sold. However, motivated by a rich cross section but short time series of matched housing transactions to buyer and seller income, we estimate filtering using an alternative approach. We difference across the log-incomes of the buyer and the seller *on the same transaction*. This approach can be implemented where only cross-sectional data are available, it does not require strong assumptions about time-invariant home attributes or implicit prices, and it relaxes the assumption that resales are necessarily random.

The data we use cover a census of housing sales from the State of Victoria, Australia (a quarter of the national population), matched to buyer and seller income. For supply constraints, we use the share of new residential development applications refused by local planning authorities who are responsible for approving new housing (the refusal rate). We leverage the fact that Victoria's topography is comparatively smooth, allowing us to sharply identify the effects of (regulatory) supply constraints as opposed to natural barriers to new construction (Saiz, 2010).[6] This is especially so in urban areas, such as Greater Melbourne, where there is significant variation in supply constraints, but little variation in natural barriers that would otherwise preclude the building of new homes.

The second reason our data are ideally suited to quantify the effect of supply constraints on filtering is that a significant local planning reform was introduced in Victoria. The reform, *VicSmart*, provides exogenous variation in how tightly local planning authorities implemented supply constraints, as observed in their heterogeneous responses to the reform. We exploit this heterogeneity, together with data from historical voting patterns, to instrument for the refusal rate using an identification strategy motivated by Hilber and

of affordability, such as the rental cost of housing are also clearly important (Molloy et al., 2022). In the presence of rental and credit market frictions, both measures matter.

[5]Most homes are only sold infrequently. The average turnover rate for homes in Australia and the US is about six percent. See, for example, Leal, Parsons, White, and Zurawski (2017).

[6]Significant parts of Victoria are unhindered by natural barriers to new construction that could otherwise constrain the supply of new homes. We substantiate this claim formally in our robustness checks, where we control for hydrological features (areas covered by water) and variability in ground surface point elevation.

Vermeulen (2015), as discussed in detail below.

Without controls for home attributes or supply constraints, we find significant *positive* differences in log-income when homes are transferred from sellers to buyers. The unconditional mean difference in relative income (log-buyer less log-seller income) for homes sold between 2011 and 2016 in Victoria is +15.5%. However, there is substantial spatial dispersion in the mean relative income between urban and regional areas, with greater evidence of upward filtering of homes from sellers to buyers in urban areas, as high as +36.8%.

Controlling for home attributes, we estimate a filter rate of +0.3% (+0.4%) for houses (apartments) per-home year, the marginal effect of an additional home-year on relative income for the mean home. Comparing this with estimates to a repeat-buyer-income model for the US, our estimates are higher than the average filter rate across US cities (-0.4% to -0.5%, Liu et al. (2021), Rosenthal (2014)), but lower than estimates for cities that are typically viewed as highly supply constrained such as Boston (+0.4%) or San Francisco (+0.7%).[7]

Remarkably, controlling for supply constraints using our instruments, we find that the filter rate for houses drops from +0.3% to only +0.01% per home-year. Supply constraints explain much of the fall. A one standard deviation increase in the refusal rate increases the filter rate by +0.25% per additional home-year for homes in that local planning area. To illustrate the quantitative significance of this estimate, we use a simple policy counterfactual based on the same model. Reducing supply constraints by one standard deviation across *all* local planning areas (also known as Local Government Areas) reduces the predicted mean difference in buyer and seller income from +15.5% to +6.6% across Victoria. Eliminating supply constraints altogether would imply *lower* buyer than seller income, with a predicted mean difference of -1.3%.

Given the interest on estimates of filter rates for low-income households specifically, we extend the results by examining whether supply constraints have heterogeneous effects over the relative income distribution. We model conditional quantiles of log-buyer less log-seller income and estimate an IV Quantile model within the class considered by Chetverikov, Larsen, and Palmer (2016). When supply constraints are not binding, filter rates are negative and significant for buyers with low income relative to that of sellers, precisely as theory predicts (Braid, 1984, Ohls, 1975, Sweeney, 1974). At the 0.15 and 0.30 quantiles, the estimates are about -2.0% per home-year. As buyers' income increases

[7] See Liu et al. (2021) for greater detail on filtering estimates across US cities and Gyourko et al. (2013) for evidence on supply constraints.

relative to that of sellers, however, the filter rate increases and is positive at high relative-income quantiles (positive from the 0.75 quantile and above).

The effects of supply constraints are essentially a mirror image. They are positive and significant at low relative-income quantiles before declining to zero at high relative-income quantiles. Thus, the economic incidence of supply constraints differs markedly from the locations in which they are binding. While constraints, in our data, are much more likely to bind in high-income urban areas, their effects are borne by buyers with *low* relative incomes. Thus, for policymakers looking for ways to increase filtering to low- and middle-income households, regulatory reform that relaxes supply constraints offers (another) way to make progress toward this goal.

The next section describes our approach to estimating filtering. Section 3 discusses data and identification, Section 4 our results and Section 5 robustness. We then compare our estimates with other recent findings in the literature, before conclusions are drawn in the final section.

2. Estimating Filter Rates

To estimate filter rates we use a model similar to Rosenthal (2014), and incorporate sellers. We assume buyers and sellers each have a common and an idiosyncratic income component:

$$Y_{it}^{b} = e^{\gamma_{it}^{b}} f\left(\mathbf{X}_{it}; \beta_t\right) \tag{1}$$

$$Y_{it}^{s} = e^{\gamma_{it}^{s}} f\left(\mathbf{X}_{it}; \beta_t\right) \tag{2}$$

where Y_{it}^{b} is buyer income for home i at time t, Y_{it}^{s} is seller income, and $f\left(\mathbf{X}_{it}; \beta_t\right)$ is a common unknown and potentially nonlinear function of the home, land and neighbourhood attributes captured in vector $\mathbf{X}_{it}$, with associated implicit prices vector β_t. γ_{it}^{b} and γ_{it}^{s} denote the idiosyncratic components of buyer and seller income.

Rosenthal shows that with data on the income of buyers of the same home over time, one can estimate filter rates directly by taking logs and then differencing Equation (1) each time a home is resold. For example, for homes sold in periods t and $t+\tau$, and assuming that $\mathbf{X}_{it+\tau} = \mathbf{X}_{it}$ and $\beta_{t+\tau} = \beta_t$ for all i and τ, one can directly estimate the mean filter rate over the period, $\gamma_{t+\tau}^{b} - \gamma_{t}^{b}$, using a repeat-buyer-income model. The assumptions $\mathbf{X}_{it+\tau} = \mathbf{X}_{it}$ and $\beta_{t+\tau} = \beta_t$ imply that each homes' attributes and the corresponding implicit prices are time invariant. To ensure there are sufficient observations for estimation for different values of τ, Rosenthal's approach requires a long time series of market sales (or survey) data where buyer income is observed with each transaction.

We use an alternative approach that allows one to estimate the model with cross-sectional data only, though requires data on transactions, and buyer *and seller* income. Like the repeat-buyer-income model, it does not require complete home attributes data either, but it does relax the assumptions that attributes and implicit prices are time invariant. We first log the equations for buyer and seller income, Equations (1) and (2), and then difference across them to obtain:

$$\log \frac{Y_{it}^b}{Y_{it}^s} = \gamma_t^b - \gamma_t^s + \omega_{it} \tag{3}$$

where $\gamma_t^b - \gamma_t^s$ is the mean difference in relative income at the time transactions are made (time t),[8] and where ω_{it} is a home-specific random error. Equation (3) provides a direct estimate of the filter rate from sellers to buyers, as opposed to the filter rate across buyers' income over time.[9] A positive estimate for $\gamma_t^b - \gamma_t^s$ implies homes filter up the income distribution on average at time t (to buyers with higher incomes, on average, than that of sellers), while a negative estimate would imply that homes filter down (to buyers with lower incomes, on average, than that of sellers). Theoretical models of filtering predict that $\gamma_t^b - \gamma_t^s$ should be negative (e.g., Braid (1984), Sweeney (1974)).

Equation (3) assumes buyers and sellers share the same common income component as captured in the function f, but this may be too restrictive as the common income derived for buyers moving into an area may be different to the common income derived from sellers who are moving out. We relax this assumption by assuming buyer-specific and seller-specific functions, f^b and f^s. In this case, buyer and seller income are given by $Y_{it}^b = e^{\gamma_t^b} f^b\left(\mathbf{X}_{it}; \beta_t\right)$ and $Y_{it}^s = e^{\gamma_t^s} f^s\left(\mathbf{X}_{it}; \beta_t\right)$. Taking logs, and differencing across buyers and sellers, we have up to a first-order approximation:[10]

$$\log \frac{Y_{it}^b}{Y_{it}^s} = c + \sum_{q \in \Upsilon} c_q x_{iq} + \eta_{it} \tag{4}$$

where the coefficients of interest are now given by the attribute coefficients ($c_q := \left(\overline{f_{x_q}^b / f^b} - \overline{f_{x_q}^s / f^s}\right)$ for each $q \in \Upsilon$, and where Υ is the set of included home attributes

[8] Throughout, we measure the time of the transaction using the date that contracts are signed.

[9] More precisely, real buyer incomes, see Rosenthal (2014).

[10] Note we are taking the approximation around the mean home, with the approximation remainder subsumed in the regression residual. We use the first-order approximation to motivate the approach. Of course, higher-order approximations could be considered as well.

and c is a reduced form constant.[11] Attributes can include variables like the age, location, size and type of home sold, permitting direct estimates of how filtering varies across home attributes and locations. By including home age (hereafter age) specifically, we can directly estimate the seller to buyer filter rate per home-year and compare this with estimates from the repeat-buyer-income model (Rosenthal, 2014, Liu et al., 2021).

2.1. Supply Constraints

Equation (4) does not identify the effects of supply constraints. They can affect both the distribution of home quality and price, and thus the rate at which homes filter across the income distribution. Motivated by existing theoretical models of filtering, we posit that supply constraints perturb the rate at which homes filter as they age:[12]

$$\log \frac{Y_{it}^{b}}{Y_{it}^{s}} = c + \sum_{q \in \Upsilon \backslash age} c_q x_{iq} + c_{age} age_{it} + c_{age,SC} \left(age_{it} \times SC_g \right) + \zeta_{it} \tag{5}$$

where we now distinguish between the set of home attributes excluding age ($\Upsilon \backslash age$), age itself (age_{it}), and the interaction between age and supply constraints in the local planning area in which the home is located ($age_{it} \times SC_g$), where SC_g measures supply constraints in local planning area g.[13] The only difference between Equations (5) and (4) is the inclusion of the interaction effect between supply constraints and age. One might conjecture that the coefficient on the interaction term ($c_{age,SC}$) is positive, implying that more restrictive supply constraints reduce the extent to which homes filter down the income distribution. Indeed, if this coefficient is sufficiently large, homes could filter upwards.

2.2. A Conditional Filtering Distribution

Equations (4) and (5) use first-order approximations of the difference in log-buyer and log-seller income around the mean home. However, as noted above, much of the debate on housing affordability focuses on whether low- and middle-income households can purchase housing. To allow for variation in filter rates over the conditional distribution of relative

[11] Note that $\overline{f^j}$ denotes the value of f^j evaluated for the mean home (i.e. the point around which the approximation is taken) and $\overline{f}^{j}_{x_q}$ is the first partial derivative of f^j with respect to the q^{th} home attribute (x_q) again evaluated at the mean home for $j \in \{b, s\}$, and j is the index denoting buyers (b) and sellers (s) respectively. If filter rates are constant across home attributes and locations the c_q coefficients are all zero, and so the more general specification collapses back to Equation (3).

[12] This assumption is motivated by theoretical models of filtering, where constraints on new supply can affect the rate at which homes filter down the income distributions. See, for example, Sweeney (1974) and Braid (1984).

[13] ζ_{it} is the regression residual with the supply constraints interaction.

income (log-buyer less log-seller income), we use the quantile regression analog for (4), where the u^{th} conditional quantile is modelled as:

$$Q_{y_{it}|\mathbf{x}_t'}(u) = c(u) + \sum_{q \in \Upsilon} c_q(u)\, x_{qt}(u) + \epsilon_{it}(u) \tag{6}$$

for $u \in \mathcal{U}$ and where $Q_{y_{it}|\mathbf{x}_t'}(u)$ denotes the u^{th} conditional quantile of relative income ($y_{it} := \log \frac{Y_{it}^b}{Y_{it}^s}$) and $\mathbf{x}_t'$ denotes the vector of included home attributes. $c(u)$ is now a quantile-specific constant, $c_q(u)$ the quantile-specific home attribute coefficient for each $q \in \Upsilon$, and $\epsilon_{it}(u)$ the quantile-specific residual. Equation (6) can be viewed as a set of local approximations, one for each quantile of an underlying conditional filtering distribution.

Equation (6) can also be modified to capture the effects of supply constraints through their interaction with age. Including attribute controls that can vary across local planning areas, we can re-parameterise Equation (6) to obtain a quantile model within the class proposed by Chetverikov et al. (2016). The u^{th} conditional quantile is now:

$$Q_{y_{it}|\mathbf{x}_t', SC_g}(u) = c_g(u) + \alpha_g(u) \times age_{it} + \sum_{q \in \Upsilon \setminus age} c_{gq}(u)\, x_{iq}(u) + \nu_{it}(u) \tag{7}$$

$$\alpha_g(u) = c_{age}(u) + c_{age,SC}(u) \times SC_g + \varepsilon_g(u) \tag{8}$$

for each quantile $u \in \mathcal{U}$ and local planning area $g = 1, \ldots G$. This model is quite general allowing for distinct attribute coefficients for homes sold in each local planning area, and across each quantile. The linear effect of age by quantile and planning area, $\alpha_g(u)$, comprises a common quantile-specific filter rate, $c_{age}(u)$, the local planning area effect of supply constraints, $c_{age,SC}(u) \times SC_g$, and an unobserved local-planning-area fixed effect, $\varepsilon_g(u)$, that *does not* depend on supply constraints.[14]

3. Data and Identification

The housing transactions data are a census of all homes sold between 2011 and 2016 from the State of Victoria, covering approximately a quarter of the Australian popula-

[14] Following Chetverikov et al. (2016), we estimate this model in two stages. First, we estimate Equation (7) for each quantile and local planning area as standard quantile regressions to estimate the linear age coefficient, $\widehat{\alpha}_g(u)\ u \in \mathcal{U}$, using the transaction and income data for each local planning area $g = 1, \ldots, G$. In the second-stage, we estimate Equation (8) where the dependent variable is the $G \times 1$ vector $\widehat{\alpha}_g(u)$ estimated from the first stage, which is regressed against the measure of supply constraints SC_g and a constant $c^{age}(u)$, again for each quantile $u \in \mathcal{U}$. Estimates from (7) and (8) provide a flexible method for quantifying whether supply constraints have heterogeneous effects over the relative income distribution.

tion.[15] To match housing transactions to buyer and seller income, the transactions data are first matched to persons using the name and addresses of each individual recorded on the change of property title for each housing sale. This matching is undertaken by the national statistical office, and the overall unique match rate is high when compared with comparable international studies (about 68%).[16]

We then compute buyer and seller income by summing across the income of all individuals involved on each side of the transaction (buyers and then, separately, sellers), using annual income reported in individual tax filings measured at the mid-point of the calendar year in which the transaction took place.[17] We restrict attention only to transactions with up to two buyers and two sellers (the vast majority of transactions) and only include transactions where both parties (buyers and sellers) have positive income. We apply a number of additional filters to the data excluding atypical housing transactions – the bottom 1% and top 1% of transactions by price and very large or small homes based on their lot size, internal area and the number of bedrooms (full details are provided in online Appendix A.1). One year of the data, 2016, has additional information on the age of each home sold that we exploit when estimating filter rates below.

Table 1 reports summary statistics for our main estimation sample. The mean house age is approximately 40 years, and the mean apartment age 27 years. Mean lot size (for houses) and building area (for apartments) are 650 sq. metres (777 sq. yards) and 95 sq. metres (114 sq. yards). The mean number of bedrooms is just over 3 for houses and 2 for apartments.

[**Table 1 about here.**]

Figure 1 shows the unconditional mean difference in relative income, by local planning area – also known as Local Government Areas (or LGAs) – over the full 2011-2016 sample. There is substantial spatial variation in the unconditional mean. For LGAs in the lowest decile, it varies from -0.057 log points (log-buyer income lower than log-seller income) to +0.048 log points (log-buyer income higher than log-seller income), whereas for LGAs in the highest decile the log-income difference ranges from +0.276 to +0.368 log points.

[15] These data are sourced from state-level administrative data. See Appendix A.

[16] The matching is undertaken by the Australian Bureau of Statistics (ABS). In a comparable exercise, Bayer et al. (2016) achieve a unique match rate of about 55% using housing transactions and mortgage data for the San Francisco Bay Area. The higher matching rate here may, in part, be explained by the ABS having access to multiple government administrative databases, including census records, that permit more accurate matching of names and addresses.

[17] We use total annual before-tax income. Tax returns are filed at the individual level in Australia each financial year.

There is evidence of clustering in the unconditional mean across LGAs in urban areas, with log-buyer income relatively higher in Greater Melbourne when compared with regional LGAs outside of Greater Melbourne.

[Figure 1 about here.]

3.1. Measuring Supply Constraints

We measure supply constraints using the local planning area (hereafter LGA) refusal rate – the share of planning applications between 2007 and 2016 that are refused by each Local Government. A similar approach to that used by Hilber and Vermeulen (2015), this is a direct measure of supply constraints on the development of new housing.[18]

Planning applications include a broad range of residential development activities including: applications to build new homes; subdivide land and/or buildings; demolitions; the development of new and vacant land; land clearing; vegetation removal and applications to build new or extend existing home structures. We measure the refusal rate by LGA including all applications assessed between 2007–2016, and excluding applications that lapsed, were withdrawn or where no final determination was made (see Appendix A.2).[19]

Table 1 reports the mean (3.1%) and standard deviation (2.3%) of the LGA refusal rate, as well as the 5th (0%) and 95th (8%) percentiles. Figure 2a reports the corresponding spatial heat map. While most planning applications are approved, there is considerable heterogeneity in the refusal rate across LGAs in Victoria and even within Greater Melbourne.

[Figure 2 about here.]

3.2. Identification

One could proceed by estimating the effects of supply constraints by including the refusal rate directly in Equations (5), or (7) and (8), without further adjustment. However, this measure of supply constraints is likely to be endogenous. Buyers with relatively high incomes can choose to purchase in LGAs with high refusal rates that restrict growth in

[18] There are 79 Local Governments responsible for assessing planning applications in Victoria. The data are recorded at the application level and each Local Government is required to report application outcomes as required by statewide legislation.

[19] Note the planning applications data we draw from go through to 2019, and so nearly all applications within the 2007-2016 sample have been assessed.

local population and housing density, which they value (Gyourko et al., 2013). Alternatively, areas with high demand for planning permits could have Local Governments that refuse a greater share of applications if they have insufficient resources to assess them.

To adjust for these (and other potential) sources of endogeneity, we draw on previous work by Hilber and Vermeulen (2015). Their identification strategy is based on the introduction of planning targets in England, and historical voting shares, which are used to identify the causal effect of supply constraints on housing price demand elasticities. Hilber and Vermeulen's approach is relevant in our context as the British and Australian planning systems share a common ancestry, and so one might expect a similar identification strategy is valid. Like them, we exploit a local planning reform that isolates exogenous variation in supply constraints across LGAs.[20]

3.2.1. The introduction of VicSmart

On 19 September 2014, the *VicSmart* planning reform took effect in Victoria. The reform altered how Local Governments assess simple planning permit applications that are deemed eligible for '*VicSmart* consideration' under the reform by: i) substantially reducing the time it takes to assess an application to 10 business days;[21] ii) removing the ability of third parties to lodge an objection or appeal any planning decision made;[22] and iii) reducing Local Government discretion to refuse them. Not all applications became eligible for *VicSmart*, but those that did include simple land subdivisions, new constructions or extensions up to a given threshold value, and permits for vegetation removal.[23]

The first instrument considered is the change in the mean decision time for all planning applications assessed before the reform (i.e., 1 Jan 2007–18 Sep 2014) and after it took effect (19 Sep 2014–31 Dec 2016). For Local Governments that were more restrictive prior to *VicSmart*, we expect larger declines in the mean decision time after the reform. For those that were less restrictive, we should see little change.

[20] One difference between our application and that of Hilber and Vermuelen is that in our case Local Governments have to comply with the reform as it is enforced through legislation. In Hilber and Vermeuelen's application, planning targets were announced by the central government and were supported by implicit sanctions such as withholding financial resources from local planning authorities that did not comply with the targets announced (Hilber and Vermeulen, 2015).

[21] This is a short period for assessing eligible applications. For context, the mean LGA decision time across all applications fell by 24 days after the introduction of the reform. More generally, prior to the reform, applications could take anywhere from a few weeks to half a year (and in some cases longer) for a decision to be made.

[22] Objections can be lodged when an application is made. Appeals (made to a statewide tribunal) can be lodged after a planning decision has been made to seek to overturn the Local Government's original decision.

[23] See Appendix A.3 for full details.

The second instrument exploits the identification strategy of Hilber and Vermeulen (2015), whereby planning authorities face strong incentives to substitute across different types of regulatory supply restrictiveness when faced with a reform that limits their ability to delay or refuse new residential development. For example, as a response to the *VicSmart* reform, Local Governments can maintain overall supply constraints by becoming *more* restrictive when assessing applications that were ineligible for consideration under *VicSmart*. We use the change in the mean refusal rate for all applications assessed by LGA, before and after the reform, using the same sample periods as those used to calculate the change in mean decision time. If Hilber and Vermeulen's theoretical motivation is correct, we should see refusal rates that increase (or at least fall by less) in LGAs where supply constraints are implemented more tightly.

The left-panel of Figure 2b shows a scatterplot of the mean refusal rate by LGA against the change in the mean decision time calculated before and after *VicSmart*. Most LGAs experienced a substantial fall in their mean decision time (on average by 24 days) after the reform, a decline that is negatively and significantly correlated with the refusal rate by LGA over the full sample period (2007-2016). The right-panel of Figure 2b shows how the average refusal rate each quarter changes over time. Not only does the quarterly refusal rate not fall after the reform, it *increases* sharply in the quarter directly after the reform took effect.[24]

3.2.2. Historical Voting Shares

One concern with these instruments is that Local Governments facing high demand for applications and with limited resources to assess them may have also responded to *VicSmart* heterogeneously.[25] To address this, the third instrument we consider uses separate information – historical voting shares. As discussed in Hilber and Vermeulen (2015), voting preferences over the two major national political parties are likely to be correlated with preferences for more or less restrictive housing supply. To ensure exogeneity, it is important that voting shares for national elections are used, as outcomes from sub-national State or Local Government elections may be directly impacted by local planning issues.

We use voting shares, measured on a two-party-preferred basis for the Liberal-National Coalition and the Australian Labor Party, from the 2001 national election as our primary

[24]It remains persistently higher thereafter, precisely as one would expect if planning authorities have *permanently* changed their assessment behaviour as an equilibrium response to the reform.

[25]For example, to comply with the shorter decision times required, it is possible Local Governments may have employed more labour and capital to assess applications more quickly, or increased their refusal rate of non-eligible applications to help meet the new requirements.

voting instrument. This election is held well before our main estimation sample, but still allows accurate geographic matching of voting shares by polling booth to voting shares by LGA.[26] In our robustness checks, we also reports results using voting shares from national elections held in 1998, 2004 and 2007.

4. Results

4.1. Filtering without controlling for supply constraints

We first report filter rate estimates without controlling for the effects of supply constraints, using Equation (4). The dependent variable is relative income, and the included covariates are age (sale year less construction year), the square of age, the number of bedrooms, and a measure of home size (for houses, the log lot size, for apartments the log of internal area).

Table 1b reports estimates of the filter rate per home-year – the marginal effect of age on relative income evaluated at the sample mean ($c_{age} + 2c_{age^2} \times \overline{age}_{it}$),[27] estimated on the samples of house transactions and apartment transactions. The results in Table 1b show the filter rates for houses and apartments are significant at +0.32% and +0.44% per home-year, implying homes filter *up* the income distribution as they age. Columns 2–3 and 5–6 show that neither demand for second-homes (investor purchases) nor downsizing sales are sufficient to explain the upward filtering observed.[28]

How do these estimates compare with those for the US? Rosenthal (2014) estimates a mean filter rate of -0.5% per home-year for owner-to-owner transitions, while Liu et al. (2021) estimates filter rates varying from -1.6% to +0.7% per home-year across US Metropolitan Statistical Areas and a similar mean to Rosenthal's overall (-0.4% per home-year). Thus, while our estimates are higher than the average across US cities, they are lower than estimates for cities typically viewed as highly supply constrained such as San Fransisco (+0.7%) or Boston (+0.4%) (see Liu et al. (2021) and Gyourko et al. (2013)).

[26]Local Government electoral boundaries are different to national election voting boundaries and determined by two separate electoral commissions at the national and state level.

[27]c_{age} and c_{age^2} denote the linear and quadratic coefficients on home age; $\overline{age}_{it}$ is the corresponding sample mean. In practice, we find a second-order polynomial in age is sufficient to accurately characterise the nonlinear effect of age on relative income – a result that is also found by Liu et al. (2021).

[28]Investor purchases are defined as transactions where the buyer reports that the home purchased will not be their principal place of residence. Downsizing is defined as transactions where the average age of the sellers is 65 years or older, the age at which individuals became eligible for the government pension.

4.2. Supply Constraints and Filtering

We now control for supply constraints. We first estimate Equation (5) allowing for the interaction between the refusal rate and age. Column 1, Table 2, reports estimates using OLS and the subsequent columns using various IV specifications – column 2 where all instruments are used (the change in mean decision time before and after *VicSmart*, the change in the refusal rate before and after *VicSmart*, and the 2001 national election two-party-preferred voting share), and subsequent columns excluding one instrument at a time.

Instrumenting for the effects of supply constraints results in much lower estimates of upwards filtering, and in some cases even downward filtering. Across specifications, we see that the filter rate drops markedly from +0.34% under OLS to only +0.008% when including all instruments with IV. This difference is large. A one standard deviation (2.27 percentage point) increase in the refusal rate increases the filter rate by +0.25% per home-year. The estimates are similar across IV specifications, and when considering a broad set of robustness checks reported in Section 5.

Estimates from the first stage, the lower panel of Table 2, show each instrument is significant in explaining the interaction between the refusal rate and age, and tests of the null of weak instruments are strongly rejected.[29] The sign of each planning instrument accords with their theoretical interpretation. LGAs that had a high refusal rate, and so implemented supply constraints tightly, experienced a greater reduction in the mean decision time after *VicSmart*. They also increased their refusal rate of applications that were *ineligible* for consideration under *VicSmart*.

Figure 3a (IV Quantile Estimates) shows how the previous results can be extended by modelling quantiles of the conditional filtering distribution of relative income, Equations (7) and (8), and using the IV Quantile estimator of Chetverikov, Larsen, and Palmer (2016). Remarkably, we now see the first direct evidence of a filter rate that accords with the theoretical predictions of filtering models. At the 0.15 and 0.30 relative income quantiles, filter rates are significant and negative, at approximately -2% per home-year in the absence of supply constraints (Figure 3a, left-panel). When measured relative to the income of sellers, homes filter quickly down the income distribution for low-income buyers. As we move to higher relative income quantiles, the filter rate increases and is close to zero at the 0.75 quantile and positive (though insignificant) at the 0.9 quantile.

[29]We report heteroskedastic-robust weak instrument test statistics (Andrews, Stock, and Sun, 2019, Montiel Olea and Pflueger, 2013).

[Figure 3 about here.]

If we consider how supply constraints affect the filter rate across the relative income distribution (Figure 3a, right-panel), we see something close to the mirror image. Supply constraints have positive and significant effects on low-income buyers (measured relative to that of the sellers) with their marginal effect on the filter rate estimated close to +0.12% per home-year in response to a one standard deviation increase in the LGA refusal rate at the 0.15 and 0.3 quantiles, but dissipating to zero at high relative income quantiles. Thus, while supply constraints may be more binding in urban areas where buyers have higher relative income, the estimated marginal effects are in fact larger for buyers with *low* relative income.

4.3. Policy Counterfactuals

The previous estimates show supply constraints explain upward filtering from sellers to buyers. But just how important are they?

Here we provide a simple policy counterfactual. Using the IV specification with all instruments from Table 2 (column 2), we calculate the predicted mean difference in relative income if supply constraints were reduced across all LGAs by one standard deviation, by two standard deviations, and when removed altogether (refusal rates across all LGAs are zero). These calculations should be interpreted cautiously. As noted in Hilber and Vermeulen (2015), they do not capture a full structural analysis nor do they account for potential substitution (or general equilibrium) effects across LGAs. Nonetheless, they do illustrate how important the effects of supply constraints on filtering can be.

The first row in Figure 3b (Policy Counterfactuals Table) shows the predicted mean difference in relative income is +15.5% for the benchmark model. Reducing supply constraints by one standard deviation reduces the predicted difference to +6.6%, two standard deviations to +2.0%, and removing supply constraints altogether to -1.3%. In the absence of supply constraints, sellers would have higher incomes on average than buyers. These effects are estimated to be be *larger* when additionally controlling for time and postal code fixed effects (see row 2 of Figure 3b).

Why is the marginal effect of reducing supply constraints nonlinear? In part, this is explained by the fact that refusal rates are bounded below at zero. However, this is not the sole explanation. The interaction between the distribution of age and supply constraints is also important. Specifically, positive skewness in the distribution of home age interacts with the fact that older homes are frequently sold in supply constrained areas.

The histograms (densities) of predicted relative income values in Figure 3b illustrate this. Those in the left-panel graph the predicted density of relative income in the IV model with all instruments, and the corresponding counterfactual prediction density when reducing the refusal rate across all LGAs by 1 standard deviation. The right-panel shows a similar comparison, but now the counterfactual density is calculated when reducing the refusal rate across all LGAs by 2 standard deviations.[30] The difference between the predicted and counterfactual densities in each case shows that supply constraints not only raise the predicted mean difference in log-buyer and log-seller income, but induce significant positive skewness in the relative income distribution as well.[31]

5. Robustness

We consider a battery of robustness checks with full results reported in Appendix B. In Table B1 columns 1 to 4, we present results including postal code fixed effects to control for unobserved local area heterogeneity in buyers and sellers and using a more narrow measure of the refusal rate.[32] The results are both qualitatively and quantitatively similar and, if anything, strengthen our earlier findings with the filter rate (excluding the effects of supply constraints) now estimated to be negative across specifications.

In columns 5 and 6 of Table B1, we consider whether there are differences in the effects of supply constraints between urban and regional areas. Restricting the sample to LGAs in Greater Melbourne only, our results are essentially unchanged. Using only LGAs outside of Greater Melbourne (regional LGAs), however, we find much smaller effects – a result corroborating the findings of Hilber and Vermeulen (2015). Supply constraints bind in urban areas and increase the relative income difference between buyers and sellers, but are less binding in regional areas and so have little impact there.

Table B2 provides additional specification checks. First, we control for both postal code and time (quarter) fixed effects jointly to ensure that hot and cold markets within the year are not affecting the results (Ngai and Tenreyro, 2014). Second, we measure and instrument for refusal rates at a more disaggregated geography (at the neighborhood level as opposed to the LGA-level).[33] This controls for Local Governments that may implement supply constraints heterogeneously *within* their own local planning area. Third, we control

[30] In both cases, refusal rates are bounded below at zero.

[31] This can also be observed in Figure B1, Appendix B, which shows the contribution of age to filtering with and without supply constraints.

[32] We exclude broader application categories such as vegetation removal and multi-category applications.

[33] To define neighborhoods, we use the Statistical Area 2 (SA2) geography constructed by the national statistical office (the ABS). There are 462 SA2s in Victoria as opposed to 79 LGAs.

for changing neighborhood characteristics over time across LGAs. We do so using the percentile change in an index of relative socioeconomic advantage and disadvantage by LGA, a proxy for whether neighborhoods were becoming more or less desirable over time.[34] Fourth, to capture spatial differences in the demand for homes that may be driven by proximity to Greater Melbourne, we also include the distance to Melbourne's core as an additional control.

The results in all cases are again similar. Estimates of the filter rate, excluding supply constraints, vary from -0.40% to -0.04%, and the estimated marginal effect of a one standard deviation increase in the refusal rate on the filter rate ranges from +0.27% to +0.47% per additional home-year. We also substantiate the claim in the Introduction that our findings are not driven by differences in local topography that can also act as a barrier to new construction. In the IV specification we include additional controls for the share of each LGA covered by water bodies (e.g. lakes, rivers, dams, flats subject to inundation and other hydrological features) and variation in ground surface point elevation by LGA.[35] Again, the results are similar (see column 5 in Table B2).

We assess the validity of our planning instruments, by using placebo checks that change the implied date that *VicSmart* took effect. The first check brings the date forward by one year (using 19 September 2013 as opposed to 19 September 2014). The second uses the date that the *VicSmart* reforms were announced (07 June 2012), and the third the date that a state government advisory committee was formed with the intent to review local planning laws (14 June 2011). The results, Table B3, show the strength of the planning instruments, as measured by the Effective F-statistic, essentially disappears once any of these alternative timings are used.

To assess the validity of the two-party-preferred (TPP) vote share from the 2001 national election, we also use TPP voting shares from three other national elections prior to our estimation sample – 1998, 2004 and 2007. The results are similar, regardless of the election used (Table B4).[36]

[34]Between 2011 and 2016, we measure the change in each LGA's relative percentile using the Index of Relative Socioeconomic Advantage and Disadvantage (IRSAD). IRSAD percentiles are calculated by the ABS using principal components on a range of socioeconomic household characteristics such as income, skilled occupations, education, employment etc. Index percentiles are calculated at the sub-neighborhood level (Statistical Area 1 geography, a sub-unit of SA2s) and then re-weighted to LGA percentiles using sub-neighborhood population shares.

[35]See, for example, Saiz (2010).

[36]One should expect this if there is a persistent underlying correlation between national voting preferences and household preferences over local supply restrictiveness at the Local Government level.

6. Comparing Findings

The above results corroborate findings from Rosenthal (2014) and Liu et al. (2021) who document significant effects of price appreciation on filtering rates, including upward filtering as we find, but who do not identify the causal impact of supply constraints. We find that supply constraints not only slow the filtering of homes down the income distribution, but are sufficiently strong to produce upward filtering.

Another closely related paper is Molloy, Nathanson, and Paciorek (2022), who consider how rental prices, housing structure, lot size and population growth vary with supply constraints in the US. Interestingly, they find little evidence that supply constraints significantly alter these outcomes, whereas we do find strong evidence that supply constraints affect filter rates as homes are transferred across the income distribution. The differences in results suggests that further research on understanding the heterogeneous effects of supply constraints on ownership and rental markets is important for quantifying their overall effect.

Our work is also connected to new findings on the effects of new construction on filtering through migration chains (Mast, 2021), and evidence on the effects of supply constraints on new construction (Mayer and Somerville, 2000). Our paper is unique in that, to the best of our knowledge, we are the first to directly document income differences between buyers and sellers at the time housing transactions are made, and to identify the causal impact of supply constraints on those transfers.

7. Conclusion

Using newly matched housing transactions to buyer and seller income from the State of Victoria (a quarter of the Australian population), we document significant dispersion in income differences between buyers and sellers across local planning areas. Controlling for the attributes and location of homes sold, we estimate that homes filter up the relative income distribution by +0.3 to +0.4% per home-year, on average. We find that supply constraints explain both the high mean filter rate observed, when compared with theory, and the dispersion in (log-) buyer and seller income differences across locations.

Estimating the effects of supply constraints on filtering using instruments that condition on a change in local planning laws and historical voting data, we find filter rates in locations without supply constraints are negative precisely as theory predicts. However, in locations where supply constraints bind, their effects are sufficiently strong to produce significant upward filtering of homes to buyers with higher income than their sellers. We conclude by showing significant heterogeneity in the effects of supply constraints over the relative income distribution. Buyers with low relative income are significantly impacted by them, while buyers with high relative income experience almost no effect. These results suggest reducing supply constraints offers another avenue for policymakers who are concerned with promoting the transfer of homes to low- and middle-income households.

Table 1: Descriptive Statistics and OLS Estimates of Filtering

Panel a: Descriptive Statistics

Data	Mean	S.D.	P5	P95
Planning applications (Unbalanced panel, 2007-2016)[a]				
Total No. applications = 186,042, Total No. LGAs = 79				
Ref. Rate	0.031	0.023	0.000	0.080
Δ Ref. rate	-0.004	0.026	-0.036	0.030
Δ Dec. time	-23.99	24.58	-77.14	11.12
2001 Electoral data (Total votes matched to LGAs = 2,675,481)[b]				
Total No. polling booths = 5,761, Total No. LGAs = 79				
TPP	0.53	0.13	0.26	0.75
	Detached homes		**Apartments**	
2016 Housing transactions	(N=22,237)		(N=7,402)	
& income[c]	Mean	S.D.	Mean	S.D.
Age	39.15	30.37	27.24	22.52
Bedrooms	3.15	0.64	2.27	0.70
Log lot size	6.48	0.63		
Log internal area			4.55	0.37
Log-buyer income	11.31	0.90	11.24	0.89
Log-seller income	11.16	1.04	11.19	1.05
Log price	13.17	0.55	13.11	0.48

Panel b: OLS Estimates of Filtering through Home Transfers[d]

$$\log \frac{Y^b_{it}}{Y^s_{it}} = \sum_{q \in \Upsilon \setminus age} c_q x_{iq} + c_{age} age_{it} + c_{age^2} age^2_{it} + \eta_{it}$$

	Houses			**Apartments**		
	All sales	Excl. investor purchases	Excl. downsizing sales	All sales	Excl. investor purchases	Excl. downsizing sales
Filter	0.32***	0.34***	0.22***	0.44***	0.47***	0.26***
rate (%)	(0.05)	(0.06)	(0.05)	(0.10)	(0.12)	(0.10)
P.C. fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Home attributes	Yes	Yes	Yes	Yes	Yes	Yes
RMSE	1.305	1.272	1.224	1.329	1.303	1.257
No. obs	22,237	16,349	19,678	7,402	4,982	6,533

Notes: [a] *Ref. rate* is the mean refusal rate from 2007 to 2016. Δ *Ref. rate* and Δ *Dec. time* are calculated as the change in the mean refusal rate and decision time by LGA before and after *VicSmart*. [b] *TPP* is the two-party-preferred percentage vote share measured by LGA for the 2001 national election to the Liberal-National Coalition. [c] *Log lot size* (*Log internal area*) is the natural log of the lot size (internal area) for a house (apartment) measured in square metres. *Age* is home age (in years). *Bedrooms* is the number of bedrooms. *Log price* is the natural log of the transaction price. [d] All specifications include postal code (*P.C.*) fixed effects and controls for home age; home age squared; bedrooms; and log lot size (internal area) for houses (apartments). *Excl. investor purchases* excludes transactions where the buyer declares the home purchased will not be their principal place of residence. *Excl. downsizing sales* excludes transactions where the mean seller age is 65 years or older. *Filter rate (%)* is the marginal change in log-buyer less log-seller income of an additional home-year evaluated at the sample mean reported in % points.

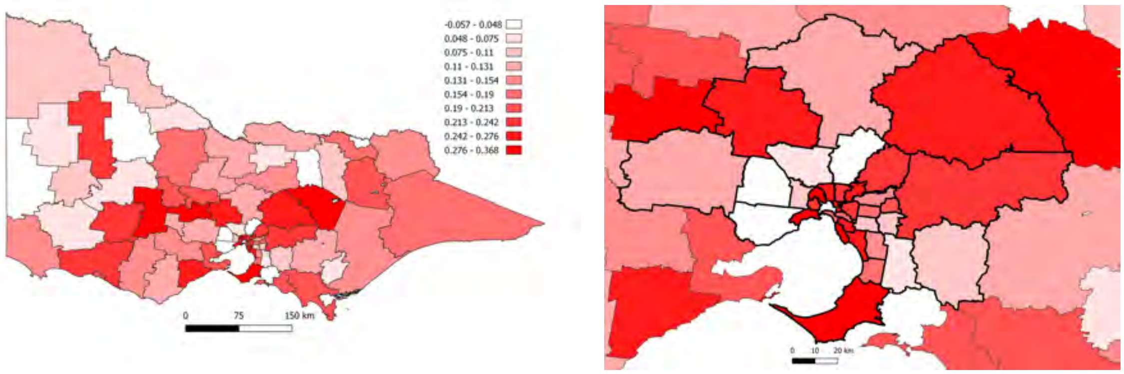
Table 2: The Effects of Supply Constraints on House Filtering

$$\log \frac{Y^b_{it}}{Y^s_{it}} = c + \sum_{q \in \Upsilon \setminus age} c_q x_{iq} + c_{age} age_{it} + c_{age^2} age^2_{it} + c_{age,SC} \left(age_{it} \times SC_g \right) + \zeta_{it}$$

	OLS	IV(TSLS) Second Stage			
N=22,237		All instr.	Excl. Δ Dec. time	Excl. Δ Ref. rate	Excl. TPP
Age	0.006***	0.001	0.0001	-0.0003	0.001
	(0.001)	(0.002)	(0.004)	(0.003)	(0.002)
Age sq.	-0.3e-04**	-0.1e-04	-0.1e-04	-9.2e-06	-0.1e-04
	(7.9e-06)	(9.9e-06)	(0.1e-04)	(0.1e-04)	(9.9e-06)
Ref. rate × Age	0.033***	0.111***	0.129**	0.137***	0.111***
	(0.009)	(0.034)	(0.064)	(0.045)	(0.034)
Bedrooms	-0.037*	-0.046***	-0.048***	-0.049***	-0.046***
	(0.015)	(0.016)	(0.017)	(0.016)	(0.016)
Log lot size	0.044***	0.063***	0.068***	0.070***	0.064***
	(0.016)	(0.018)	(0.023)	(0.020)	(0.018)
Filter rate (%)	0.34***	0.01	-0.07	-0.11	0.01
	(0.05)	(0.15)	(0.28)	(0.20)	(0.15)
M.E. of Ref. rate (%)	0.07***	0.25***	0.29**	0.31***	0.25***
	(0.02)	(0.08)	(0.15)	(0.10)	(0.08)
RMSE	1.308	1.310	1.312	1.313	1.310
		IV(TSLS) First Stage			
Age		0.049***	0.060***	0.053***	0.049***
		(0.002)	(0.002)	(0.002)	(0.001)
Age sq.		-0.0002***	-0.0002***	-0.0002***	-0.0002***
		(9.6-06)	(9.6e-06)	(9.6e-06)	(8.9e-06)
Δ Dec. time × Age		-0.0002***		-0.0002***	-0.0002***
		(0.00001)		(0.00001)	(0.00001)
Δ Ref. rate × Age		0.134***	0.098***		0.134***
		(0.011)	(0.011)		(0.011)
TPP × Age		0.000	-0.008***	-0.004**	
		(0.002)	(0.002)	(0.002)	
Bedrooms		0.108***	0.111***	0.112***	0.108***
		(0.013)	(0.013)	(0.013)	(0.013)
Log lot size		-0.205***	-0.218***	-0.209***	-0.204***
		(0.013)	(0.012)	(0.012)	(0.011)
Eff. F-stat.		147.19	54.60	142.90	213.14
5%/10%		22.55/13.97	14.15/9.46	7.46/5.52	18.75/12.16
/20% CV		/9.18	/6.74	/4.39	/8.38

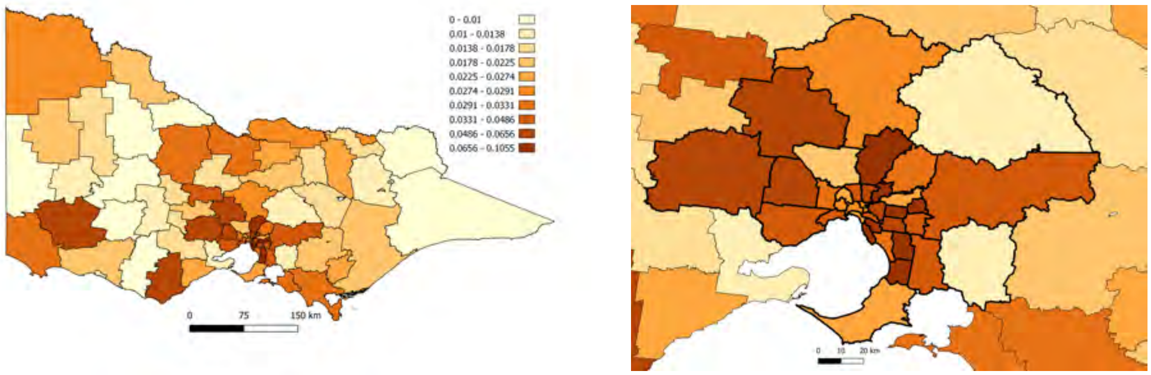
Notes: See notes to Table 1 for variable definitions, *Age sq.* is the square of age. Robust standard errors are reported in parentheses. The upper panel reports OLS and IV Two Stage Least Squares (*IV(TSLS)*) estimates from the second stage – the dependent variable is relative income. The lower panel reports estimates from the first stage – the dependent variable is *Ref. rate* × *Age*. *All instr.* includes all three instruments: Δ *Dec. time*, Δ *Ref. rate* and *TPP*. Columns 3–5 report estimates excluding one instrument at a time. *M.E. of Ref. rate (%)* is the marginal effect of a one standard deviation increase in *Ref. rate* on the *Filter rate* reported in % points. The Eff. F-stat. is from Montiel Olea and Pflueger (2013) with 5%, 10% and 20% Nagar-bias critical values (CV) with 5% size.

Figure 1: Relative Income by Local Government Area (2011-2016)



Note: The unconditional mean of log-buyer less log-seller income reported by Local Government Area (LGA)-decile for 2011-2016. *Left-panel*: deciles for the state of Victoria; *Right-panel*: Zoom to Greater Melbourne LGAs –enclosed with a bold outline.

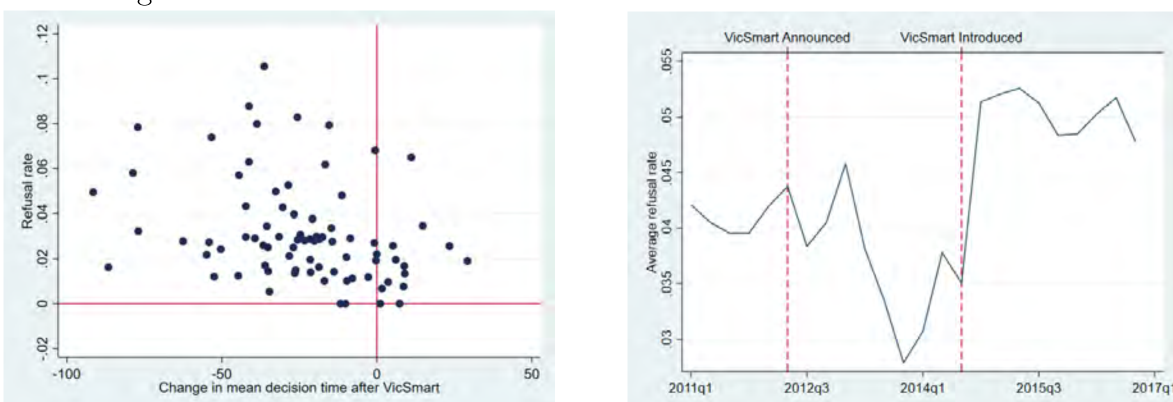
Figure 2: Refusal Rates and The *VicSmart* Planning Instruments
Panel a: Refusal Rates by LGA



Panel b: The *VicSmart* Planning Instruments

LGA Refusal Rate vs.
Change in Mean Decision Time

Quarterly Refusal Rate
Over Time

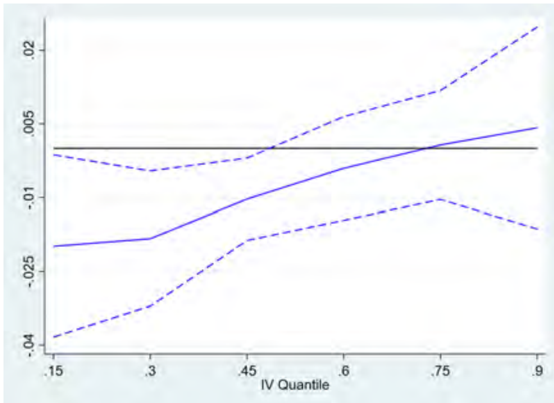


Notes: Authors calculations based on 186,042 planning applications assessed between 1 January 2007 to 31 December 2016. *Panel a*(left): LGA *refusal rate* by decile across the state of Victoria. *Panel a*(right): Greater Melbourne LGAs highlighted with a bold outline. *Panel b*(left): Scatter of the LGA *refusal rate* calculated over that period, against the *change in mean decision time* before (1 January 2007–18 September 2019) and after (19 September 2019–31 December 2016) *VicSmart*. *Panel b*(right): Average quarterly *refusal rate* over time across all Victorian LGAs.

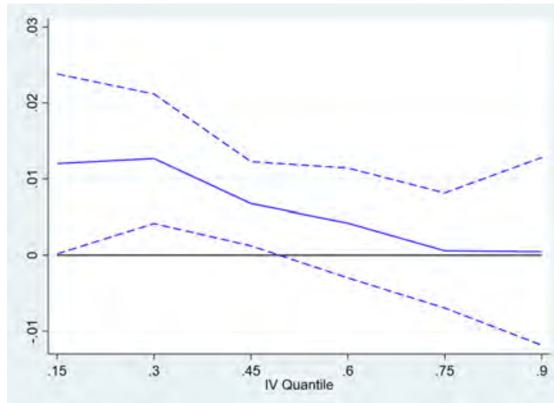
Figure 3: IV Quantile Model and Policy Counterfactuals

Panel a: IV Quantile Estimates

Filter Rate by Quantile



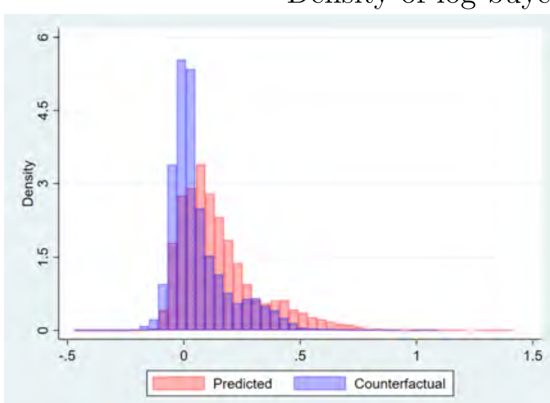
M.E. of Refusal Rate by Quantile

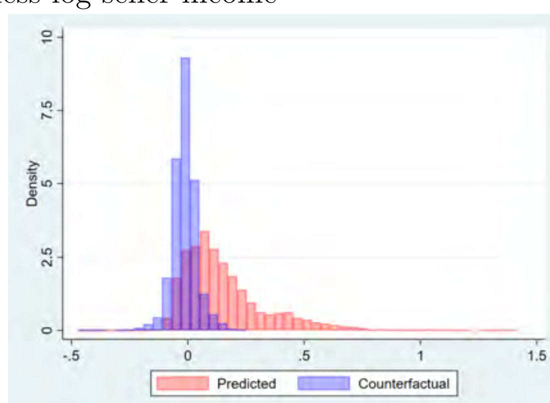


Notes: Estimates from the IV Quantile estimator (Chetverikov et al., 2016) with all instruments. *Left*: $\widehat{c}_{age}(u)$ (the age filter rate by quantile). *Right*: $\widehat{c}_{age,SC}(u)$ (the marginal effect of the refusal rate on the age filter rate by quantile). The dashed lines denote robust 90% asymptotic confidence intervals. The second stage IV estimates exclude the bottom and top 10% of LGA coefficients by quantile. The minimum (maximum) number of observations by quantile after trimming is 20054 (20927).

Panel b: Policy Counterfactuals

Density of log-buyer less log-seller income





Predicted mean of log-buyer less log-seller income N=22,237	Estimation sample	Reducing supply constraints by 1 S.D.[a]	Reducing supply constraints by 2 S.D.[b]	Removing supply constraints[c]
IV(TSLS)	0.155	0.066	0.020	-0.013
IV(TSLS) with P.C. & time fixed effects	0.155	0.045	-0.012	-0.052

Notes: *IV(TSLS)* uses the two-stage least squares model estimates reported in column 2 of Table 2. *IV(TSLS) with P.C. & time fixed effects* reports mean predictions with additional controls for postal code and time (quarter) fixed effects. [a]All LGA refusal rates are reduced by 1 standard deviation (2.27%) subject to the zero lower bound. [b]The reduction is 2 standard deviations again subject to the zero lower bound. [c]Sets all LGA refusal rates to zero. Predicted densities in the histograms are based on *IV(TSLS)*. *Predicted* is the predicted density from the *Estimation sample*. *Left*: Counterfactual density by reducing supply constraints by 1 standard deviation (as per [a]). *Right*: Counterfactual density by removing supply constraints (as per [c]).

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Online Appendixes

Appendix A. Data sources

Appendix A.1. Housing Transaction and Income Data

The housing transactions data are sourced from property title records provided by the Victorian Department of Treasury and Finance under Australian Research Council Linkage Project LP160101518: "Predicting the Value and Use of Urban Land". Income data are sourced from the personal income taxation database within the Australian Bureau of Statistics (ABS) Multi-Agency Data Integration Project (MADIP). As noted in the main text, housing transactions are matched to the MADIP spline by the the ABS in a secure data enviorment before being de-identified and accessed by the authors through the ABS DataLab portal. Further detail on the matching of transactions to buyer and seller income is provided in Appendix A.1.1. Access to the underlying unit record data is managed by the ABS and further information on obtaining access to the data is provided here: https://www.abs.gov.au/statistics/microdata-tablebuilder/datalab

Appendix A.1.1. Matching Housing Transactions to Buyer and Seller Income

To measure filtering using differences in log-income across buyers and sellers at the time transactions are made, we require matched housing transactions to the income of buyers and sellers. In consultation with the authors, this matching was undertaken by the ABS at the individual level using housing transactions (changes of property title) data provided by the Victorian Department of Treasury and Finance.

The matching algorithm is based on names and addresses recorded on the change of property title, matching to names and addresses recorded in the Multi-Agency Data Integration Project (MADIP). MADIP is a census of all individuals in Australia including those who, between 2006 and 2021, have participated in one or more off: (i) the Medicare Consumer Directory (Medicare the name of the universal national healthcare system of Australia – it covers all citizens and permanent residents); (ii) the personal income tax database maintained by the Australian Taxation Office; or (iii) the government social security (DOMINO Centrelink) database.[37]

Of the 1,996,660 unique name-address pairs identified in the housing transactions data, exact matches were found for 68.2% of records (approximately 1.36 million records). This is a high match rate by international standards. For example, Bayer et al. (2016)

[37]See Parker (2017) and https://www.abs.gov.au/websitedbs/d3310114.nsf/home/Person+Linkage+Spine for further detail.

undertake a similar matching exercise for the San Francisco Bay Area and achieve a unique match rate of about 55%. Notwithstanding, it should be noted that the housing transaction address is not always the same as the residential address of the parties in MADIP (although the high match rate does suggest a close correspondence). Moreover, housing transactions do not include other demographic information such as gender or date of birth, that have been used by the ABS in other data linkages.

Retaining transactions where all individuals (buyers and sellers) are uniquely matched, incomes for buyers and sellers are sourced from the Australian Taxation Office personal income taxation database component of MADIP. This database records total income earned before-tax (hereafter income) from tax filings by individual in each taxation (financial) year. For example, for housing transactions made in 2016, we compute total buyer and total seller income using income earned during the period 1 July 2015 to 30 June 2016 and summing across the incomes of all buyers (buyer income) and the incomes of all sellers (seller income) on each side of a transaction.

To measure buyer and seller income as precisely as possible, we restrict the sample to transactions with up to two buyers and two sellers, and where all buyers and sellers on both sides of each transaction are uniquely matched to MADIP (1,040,241 individual title changes corresponding to 277,529 unique housing transactions).[38] We further restrict the sample to transactions where buyer and seller income are positive and exclude transactions for atypical homes – measured as homes in the top or bottom 1% of the price distribution, the top 1% for bedrooms by home type – house or apartment, the top 5% in terms of lot size for houses and the top 1% in terms of internal area for apartments. This leaves us with 222,375 observations for calculating mean differences in log-buyer and log-seller income over the 2011–2016 sample. Where age of the home is required to estimate the filter rate, we restrict the sample to transactions in 2016 where data on age are available. This leaves 33,489 sales for estimation across Victoria, 22,237 of which are house sales and 7,402 are apartment sales. To get a sense of this sample size, Rosenthal (2014) uses 13,782 repeat-buyer observations for the US.

Appendix A.2. Planning Permit Data

The planning permit data are sourced from the Victorian Planning Permit Activity Reporting system (PPARs). We use planning applications where the proposed land use is

[38]Transactions with at most two buyers and two sellers make up the vast majority of transactions. Only 18,180 of 1,058,421 uniquely matched title changes involved more than two buyers or more than two sellers.

residential and exclude non-residential and mixed-use applications.[39] The application categories for proposed residential development include: single dwelling; multi-unit dwellings (e.g. apartments); subdivision of land and buildings; changes or extension of use; alterations to a building structure or dwelling; extensions; one or more new buildings; other buildings and works (including septic tanks, dams, earthworks); consolidation; demolition; native vegetation removal; other vegetation removal; subdivision - change to easement and/or restrictions or removal of covenant; subdivision – realignment of boundary and "other" which includes applications that cover multiple categories.[40] In the robustness checks (see Table B1), we also consider a more narrow set of applications excluding native vegetation removal; other vegetation removal; and the "other" categories.

When measuring the refusal rate, we use the share of all permit applications between 2007 and 2016 refused by the responsible Local Government authority. Excluded from this measure are applications that are yet to be determined, where no permit is required, the application is withdrawn by the applicant, the application lapses or where no final determination is made (these excluded categories make up 8.64% of a total 203,642 residential development applications). This leaves us with 186,042 applications to measure the refusal rate.[41]

Appendix A.3. Planning Applications that Became Eligible for VicSmart Consideration

The *VicSmart* planning reforms took effect from 19 September 2014. While Local Governments are still responsible for assessing *VicSmart* eligible applications, separate application and assessment criteria apply. *VicSmart* applications have a 10-day assessment requirment, are protected from third party objections and appeals, and have predetermined approval critieria. Applications that became eligible for *VicSmart* include: realign a boundary between two lots; subdivide land into lots each containing an existing building or car parking space; subdivide land with an approved development into two lots; construct or extend a front fence in a residential zone or overlay; construct a building or carry out works with an estimate cost of up to $50,000; construct a building or works in an overlay; remove, destroy or lop one tree; minor subdivision, minor buildings and works in a Heritage Overlay; and minor subdivision or buildings and works in a Special Build-

[39]Non-residential includes retail, office, commercial and industrial applications. Mixed-use includes, for example, homes combined with a retail or office premises.

[40]For further detail, see: Victorian Government. Planning Permit Activity Reporting: Data Dictionary. Department of Environment, Land, Water and Planning, 2016.

[41]All residential applications made through Local Governments are recorded in PPARS.

ing Overlay.[42] 10.3% of all planning applications across Victoria were *VicSmart*-eligible between 19 September 2014 and 31 December 2016. The minimum (maximum) share of applications eligible by LGA over this period was 0% (28.9%).

Appendix A.4. Federal Electoral Data

Historical data from national elections for Australia have been compiled by the authors from the Australian Electoral Commission website: https://www.aec.gov.au/. Historical two party preferred voting shares are downloaded at the pooling booth level and are matched to Local Government Areas using ABS population concordance weights. Data are compiled for the 1998, 2001, 2004 and 2007 national elections.

Appendix A.5. Hydrology and Elevation

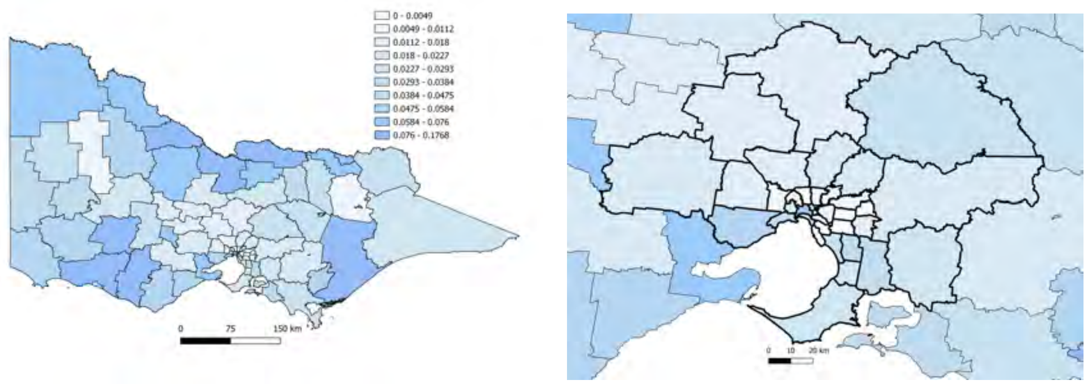
In Table B2 we include additional controls for natural barriers to new housing construction. Specifically, we include the fraction of each LGA's physical area that is covered by hydrological features such as lakes, rivers, dams and flats subject to inundation; and the standard deviation in the elevation of ground surface points by LGA. The hydrological data are sourced from VicMap Hydro Water Area Pologyons (1:25,000).[43] The elevation data are sourced from VicMap Elevation Ground Surface Point (1:25,000).[44] Maps summarising these barriers are reported in Figures A.4 and A.5.

[42]See Victorian Government. *VicSmart Planning Assessment: A New Planning Permit Process for Victoria*. Department of Planning, Transport and Local Infrastructure, 2014.

[43]See https://discover.data.vic.gov.au/dataset/water-area-polygon-1-25000-vicmap-hydro.

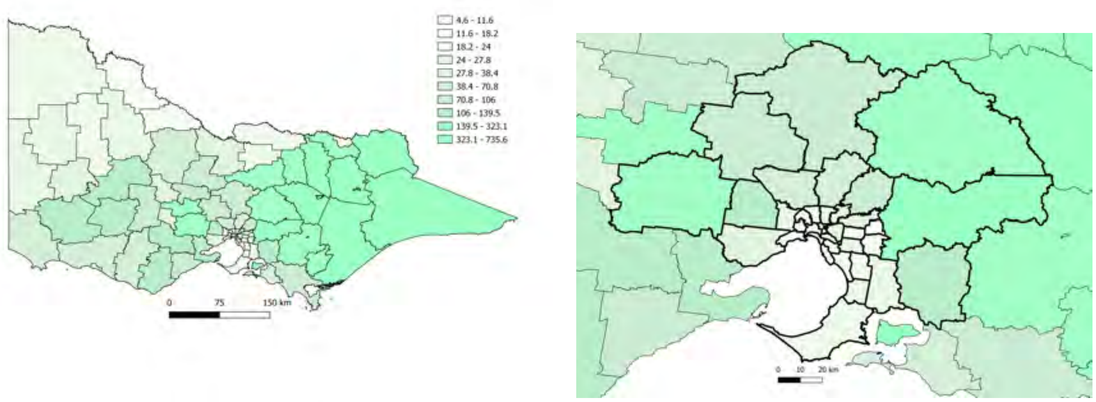
[44]See https://discover.data.vic.gov.au/dataset/ground-surface-point-1-25000-vicmap-elevation.

Figure A.4: LGA Areas Covered by Hydrological Features



Note: LGA hydrological area decile shares are reported (i.e. deciles based on the share each of LGAs physical area covered by lakes, rivers, dams and flats subject to inundation). The hydrological data are sourced from VicMap Hydro water area polygons and use data for 188,779 hydrological features in Victoria. Greater Melbourne LGAs are highlighted in the right-panel with a bold outline.

Figure A.5: LGA Standard Deviation in Ground Surface Point Elevation



Note: Dispersion in ground surface point elevation by LGA-decile is reported (measured in metres). The ground surface point elevation data are sourced from VicMap Elevation and are based on data from 334,383 ground surface control points in Victoria. Greater Melbourne LGAs are highlighted in the right-panel with a bold outline.

Appendix B. Robustness

We report a range of robustness checks discussed in Section 5 of the main text. Table B1, columns 1 to 4, re-estimates the IV(TSLS) model presented in Table 2, but now includes postal code fixed effects and uses a narrow measure of the refusal rate that excludes planning applications for vegetation removal and multiple-category applications. Compared with Table 2, we see similar findings – a small negative filter rate estimated across specifications and significant positive effects of supply constraints. Columns 5 and 6 report estimates using Greater Melbourne LGAs only and regional LGAs outside of Greater Melburne only. While the results for LGAs in Greater Melbourne are similar to the findings discussed in the main text, the effects of supply constraints in regional LGAs are essentially zero.

Table B1: Robustness Including Postal Code Fixed Effects

IV(TSLS) – Second stage, dependent variable is log-buyer less log-seller income

	All inst.	Excl. Δ Dec. time	Excl. Δ Ref. rate	Excl. 2001 TPP	All inst. Greater Mel.	All inst. Regional LGAs
Age	-0.001	-0.002	-0.001	-0.002	-0.003	0.002
	(0.003)	(0.006)	(0.003)	(0.003)	(0.004)	(0.003)
Ref. rate $\times$ Age	0.151**	0.170	0.138*	0.159**	0.152**	0.009
	(0.075)	(0.153)	(0.076)	(0.076)	(0.067)	(0.130)
Filter rate (%)	-0.22	-0.29	-0.17	-0.25	-0.42	0.27
	(0.27)	(0.55)	(0.28)	(0.28)	(0.34)	(0.28)
M.E. of Ref. rate (%)	0.34**	0.39	0.31*	0.36**	0.35**	0.02
	(0.17)	(0.35)	(0.17)	(0.17)	(0.15)	(0.30)
Eff. F-stat.	50.47	15.62	135.22	56.92	56.38	74.09
5%	28.46	25.44	13.33	27.82	29.27	26.95
/10%	/17.64	/16.09	/8.98	/17.48	/18.10	/16.48
/20% CV	/11.56	/10.77	/6.45	/11.62	/11.82	/10.65
RMSE	1.291	1.291	1.290	1.291	1.304	1.258
No. obs.	22,232	22,232	22,232	22,232	14,878	7,354

Notes: Robust standard errors are reported in parentheses. All specifications include postal code fixed effects and home attribute controls (bedrooms, log lot size, age, and age squared). The refusal rate is measured using a more narrow refusal rate that excludes applications to remove vegetation and applications covering multiple-categories. Variable labels and column headings for the first four columns are the same as those used in Table 2 (see Table 2 notes). The final two columns show estimates with all instruments but restricting the sample to Greater Melbourne LGAs only, and regional LGAs outside of Greater Melbourne only.

Table B2 reports additional specification checks using the change in mean in decision time around *VicSmart* as the only instrument. First, we include both postal code and quarter fixed effects to control for any seasonality in moving patterns as per Ngai and Tenreyro (2014) (column 1). Next we allow for heterogeneity in supply constraints *within* Local Government Areas (LGAs) by measuring refusal rates at a more disaggregated level of geography (neighborhoods also known as Statistical Area 2 or SA2s, of which there are 462 in Victoria as compared with 79 LGAs) and instrument for them using the change in the mean planning application decision time around *VicSmart* also measured at the SA2-level (column 2).

In column 3, we control for changes in the socioeconomic characteristics of households. We use the change in the LGA's relative percentile based on the Index of Relative Socioeconomic Advantage and Disadvantage (IRSAD)[45] between 2011 and 2016 interacted with age. LGAs with an increase in their relative IRSAD percentile are likely to have become more desirable over time. In column 4, we control for differences in spatial demand by including a control for the distance of each transaction to the core of Melbourne interacted with age. In column 5, we include controls for age interacted with topography by including: i) age interacted with the fraction of each LGA's physical area that is covered by water bodies (e.g. inland lakes, rivers, dams, flats subject to inundation and other hydrological features); and ii) age interacted with the standard deviation in the elevation of ground surface points within each LGA. As discussed in Saiz (2010), these two measures capture topographical constraints on building new housing supply and have proven to be accurate proxies for variation in natural supply barriers.

The results in Table B2 show similar estimates of filter rates across specifications and of the effect of supply constraints on filtering. Across all specifications, filter rates are small and negative when excluding the effects of supply constraints. In contrast, the marginal effect of the refusal rate on the filter rate is positive and significant with estimates ranging from +0.27% to +0.47% per additional home-year in response to a one standard deviation increase in the refusal rate.

[45]This index is compiled by the Australian Bureau of Statistics, see ABS catalogue: 2033.0.55.001. IRSAD percentiles are measured at the sub-neighborhood (SA1) level and are then re-weighted to LGAs using populations weights.

Table B2: Additional Specification Checks

IV(TSLS) – Second stage, dependent variable is log-buyer less log-seller income

N=22,237	P.C. & time FE[a]	SA2 Ref. rate[b]	IRSAD[c]	Dist.[d]	Top.[e]
Age	-0.003	-0.0003	0.001	-0.003	-0.003
	(0.004)	(0.004)	(0.004)	(0.004)	(0.006)
Ref. rate × Age	0.205**	0.126**	0.121**	0.184**	0.170**
	(0.092)	(0.057)	(0.057)	(0.077)	(0.082)
Filter rate (%)	-0.40	-0.08	-0.04	-0.29	-0.33
	(0.33)	(0.26)	(0.23)	(0.33)	(0.46)
M.E. of Ref. rate (%)	0.47**	0.29**	0.27**	0.42**	0.39**
	(0.21)	(0.13)	(0.13)	(0.17)	(0.19)
Eff. F-stat.	180.87	132.57	201.83	143.69	143.57
5%	37.42	37.42	37.42	37.42	37.42
/10%	/23.11	/23.11	/23.11	/23.11	/23.11
/20% CV	/15.06	/15.06	/15.06	/15.06	/15.06
RMSE	1.292	1.315	1.311	1.327	1.316

Notes: Robust standard errors are reported in parentheses. All specifications use the change in mean decision time around *VicSmart* as the included instrument. [a]Includes postal code and time fixed effects (FE). [b]Refusal rates are measured (and instrumented for) at the neighborhood (SA2) level as opposed to LGA level. [c]Controls for the change in the relative IRSAD percentile for each LGA between 2011 and 2016 interacted with age. [d]Controls for straight line distance (in metres) to the Melbourne city core (measured using the distances between the SA1 centroid in which the home is located and an SA1 centroid centered on the Melbourne CBD). There are 13,194 SA1s for Victoria represented in the sample. [e]Controls for interactions between age and topography: namely, the fraction of each LGAs' physical area covered by hydrological features including lakes, rivers, wetlands, and flats subject to inundation; and the standard deviation in ground surface control point elevation within each LGA. *M.E. of Ref. rate (%)* denotes the marginal effect of a one standard deviation increase in the refusal rate on the filter rate per home-year (measured in % points). See also the notes to Table 2.

Table B3 reports planning instrument strength using placebo checks based on the timing around which the planning instruments are calculated. We consider a date one year earlier than when *VicSmart* took effect (19 September 2013), the date when the *VicSmart* reforms were first announced (7 June 2012), and the date a government advisory committee was formed to review planning legislation (4 June 2011). We observe that the strength of the planning instruments essentially disappears once any of the alternative dates are used.

Table B4 reports IV(TSLS) results from the second stage and instrument strength when varying the national election data used according to the year that the election was held. We find similar results across multiple election years prior to our estimation sample suggesting our results are not specific to the 2001 national election only.

Table B3: Planning Instrument Relevance

IV(TSLS) – First stage, dependent variable is Ref. rate × Age

N=22,237	*VicSmart* implementation	1-year before implementation	*VicSmart* announced	Committee announced
Eff. F-stat.	75.82	5.11	0.87	0.83
5%/10%	24.85/15.74	9.87/6.93	12.30/8.37	13.77/9.23
/20% CV	/10.56	/5.22	/6.09	/6.61

Notes: All first stage regressions include postal code and time fixed effects and controls for age, age squared, log land area, and bedrooms and the change in mean decision time and refusal rate instruments (see the definitions in Tables 1a and 1b). *VicSmart implementation* denotes the change in the mean decision time and the change in the mean refusal rate are calculated around 19 September 2014, *1-year before implementation* calculates the changes in both means around 19 September 2013, *VicSmart announced* around 7 June 2012, and *Committee announced* around 4 June 2011. The Eff. F-stat. is based on Montiel Olea and Pflueger (2013) with 5%, 10% and 20% Nagar-bias critical values (CV) with 5% size.

Table B4: Election Instrument Robustness Checks

IV(TSLS) – Second stage, dependent variable is log-buyer less log-seller income

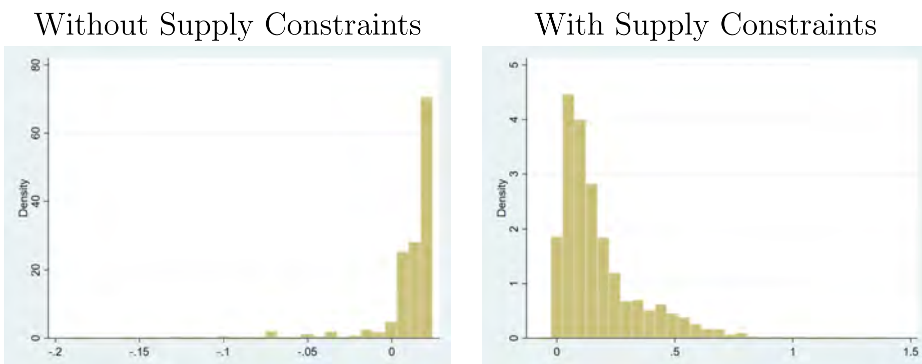
N=22,237	2001 Federal Election	1998 Federal Election	2004 Federal Election	2007 Federal Election
Age	0.001	0.003	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)
Ref. rate × Age	0.111***	0.079**	0.108***	0.110***
	(0.034)	(0.032)	(0.034)	(0.034)
Filter rate (%)	0.01	0.14	0.02	0.01
	(0.15)	(0.14)	(0.15)	(0.15)
M.E. of Ref. rate (%)	0.25***	0.18**	0.25***	0.25***
	(0.08)	(0.07)	(0.08)	(0.08)
Eff. F-stat.	147.19	167.04	150.91	150.20
5%/10%	22.55/13.97	22.17/13.76	22.19/13.79	22.31/13.86
/20% CV	/9.18	/9.06	/9.09	/9.12
RMSE	1.310	1.308	1.310	1.310

Notes: Robust standard errors are reported in parentheses. Each specification uses the two-party-preferred vote share (*TPP*) to the Liberal-National Party Coalition as per the election year listed in each column heading. In all specifications the change in mean decision time (Δ *Dec. time*) and the change in the mean refusal rate (Δ *Ref. rate*) around *VicSmart* are also included as instruments. See the notes to Table 2 and Tables B1 to B3.

Appendix B.1. Skewness and the Effects of Supply Constraints

Figure B1 reports histograms of predicted (linear) filter rates without (the left-panel) and with supply constraints (the right-panel). The comparison shows how the interaction between the age of homes sold and supply constraints generates significant positive skew in the predicted distribution of filter rates across homes.

Figure B1: Histogram of Predicted Filter Rates



Notes: Estimates are derived from the IV(TSLS) estimates with all instruments. The left-panel reports the histogram of predicted (linear) filter rates without local supply constraints (i.e. $c_{age} \times age_{it}$). The right-panel the predicted histogram using the same estimation sample when supply constraints are present (i.e. $c_{age} \times age_{it} + c_{age,SC} \times age_{it} \times SC_g$). The empirical measure of SC_g is the refusal rate by LGA.